Hierarchical Deep Learning Neural Network (HiDeNN)-AI for process design and performance prediction of scientific and engineering systems

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We propose a mechanistic Artificial Intelligence (AI) framework, called Hierarchical Deep Learning Neural Networks or HiDeNN-AI [1, 2] for discovering the mathematical and scientific principle behind engineering systems. The HiDeNN-AI discovery has three sequentially executed steps: (1) using available small amount of data to characterize an unknown physical process through simple mechanistic equation, (2) enriching the database with the mechanistic equation from (1) and training with combined data from the equation and available data to create a reduced order model with uncertainty, and (3) using the reduced order model to generate sufficient data to discover new robust mathematical and scientific principles that are able to (a) perform predictive solutions for design and optimization, and (b) provide simple relationship for online monitoring and control. We have applied this HiDeNN-AI framework to address the Air Force Research Lab (AFRL) Additive Manufacturing (AM) modeling challenges [3, 4, 5]; and for the prediction of the as-built mechanical properties [6]. To further enhance HiDeNN-AI, a reduced-order modeling method accounting input uncertainty, called the Tensor Decomposition (TD) [7], is being developed. The so-called HiDeNN-AI-TD is expected to solve the general scientific and engineering problems in high dimensional space-time-parametric domains at deep discount in computational cost. Once the offline database is set up, the mechanistic machine learning module of HiDeNN-AI can be activated for process design, real time system monitoring and control or the identification of key processing parameters for the desired performance of the manufactured material systems with uncertainty quantification. Various results comparing the HiDeNN-AI-TD approach with the conventional machine learning models will be shown using real-time IR in-situ measurement, and high-frequency thermal signatures for the predictions of mechanical properties and the detection of lack of fusion and keyhole porosities.

References

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